LSTM neural networks for bandwidth merging in multi-source seismic acquisition

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Summary

This study explores the application of Long Short-Term Memory (LSTM) neural networks for bandwidth merging of multi-source seismic data. After introducing the LSTM neural network, a novel self-supervised method merges datasets acquired using different source types with varying frequency content into a single broadband volume. In this application, synthetic data results demonstrate that the LSTM-merging algorithm achieves results that differ from the truth broadband signals in minimum amplitude distortions. The performance of this LSTM architecture is validated on synthetic datasets in this case, but applications to real datasets do not require significant modifications to the workflow presented here. The self-supervised approach minimizes the need for labels, making the training fast and the approach practical for real-world scenarios. This method streamlines the merging procedure and demonstrates the potential of LSTMs as an alternative to conventional processing workflows and methodologies.

Introduction

Deep Learning (DL) has revolutionized the field of artificial intelligence by enabling computers to learn sophisticated data representations. DL models leverage multiple layers of interconnected neurons to extract various features from datasets. These processes have been successful in fields such as Computer Vision, Natural Language Processing and Speech Synthesis (LeCun et al., 2015; Goodfellow, 2016; Schmidhuber, 2015). At the heart of DL lies the neural network, a biologically inspired computing system that mimics the structure of the human brain. While feedforward neural networks are foundational in DL, they are inherently limited in handling sequential or time-dependent data.

Recurrent neural networks (RNNs) address the limitations of feedforward architectures in handling sequential data by implementing a recurrent model in the hidden layer (Rumelhart et al., 1986; Elman, 1990). This feature enables RNNs to maintain context over time steps. As a result, RNNs are well-suited for time-series prediction and analysis. However, the gradients for RNNs are time-dependent. Consequently, problems in the training procedure arise since the gradients tend to decrease or blow up as they propagate backward through time (Bengio et al., 1994; Hochreiter, 1998).

A more sophisticated neuron capable of overcoming the gradient vanishing and exploding problems was developed by Hochreiter (1997) and called Long Short-Term Memory (LSTM) networks. LSTM incorporates the concept of cell states and gating mechanisms to regulate the flow of information and gradients across time steps. The cell state vector $\mathbf{C}_t$ allows the information of long-term dependencies and correlations to flow with minimal modifications across different time steps. The forget gate ($\mathbf{f}_t$), input gate ($\mathbf{i}_t$) and output gate ($\mathbf{o}_t$) operate through matrix-vector multiplications to discard or enhance short-term features and dependencies. The $\mathbf{C}_t$ and different gates update the hidden unit $\mathbf{h}_t$ at each time step and hidden layer.

Recently, LSTM and, more generally, RNN have gained momentum in seismic research through applications such as inversion, signal processing and interpretation. A prestack time migration velocity analysis method using RNNs was proposed (Pereg et al., 2020). Gao et al. (2021) introduced a

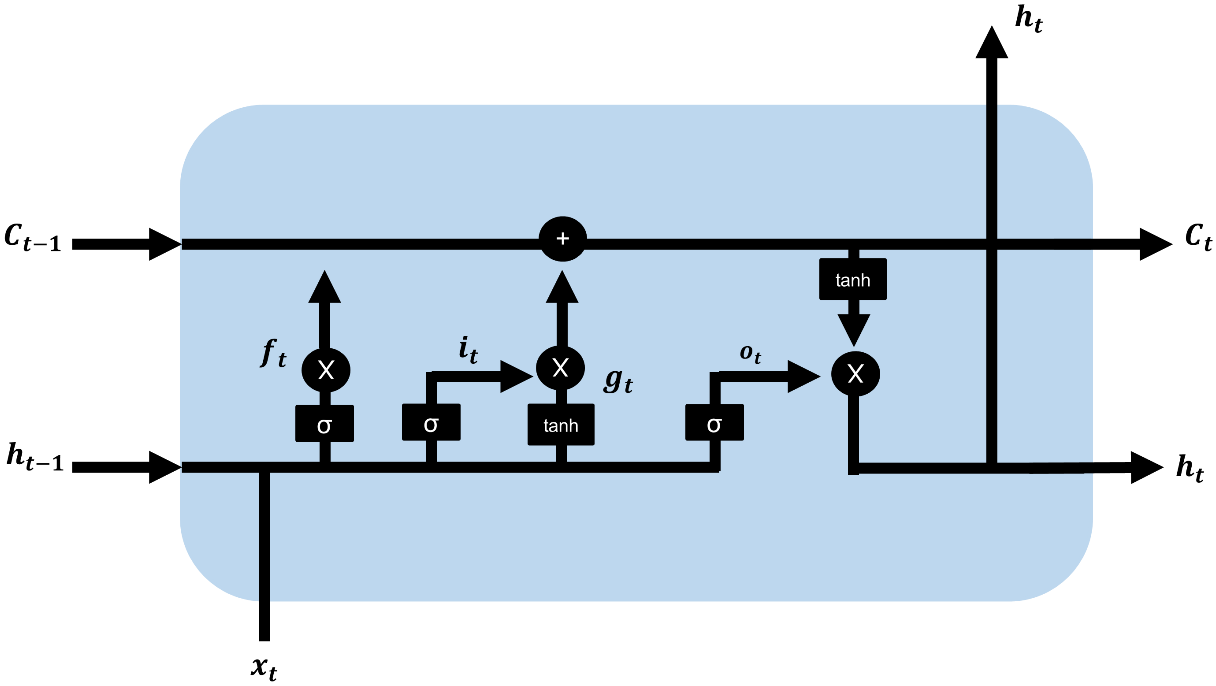

Figure 1: General representation of a single LSTM neuron. The cell state $\mathbf{C}_t$ allows the flow of information of long-term dependencies across several time steps. The different gates control the short-term dependencies to update the hidden unit at each time step $\mathbf{h}_t$.

hybrid approach using an LSTM-based data correction to account for the portions of the data not adequately represented by the convolutional model. Another application leverages RNNs to automatize Normal Move Out (NMO) correction, significantly reducing human intervention and computational time (Biswas et al., 2019). LSTM applications for merging GPR data and deconvolution of seismic data have also been proposed (Roncoroni et al., 2024b,a).

This study proposes using LSTM networks to merge seismic from three surveys acquired by implementing three different source types in the field. Multi-source (or multi-voice) acquisition happens naturally when field restrictions do not allow using the same source or source type in a given area. A different application for merging seismic data is the case in which vintage and new datasets must be combined into a single volume. These situations usually require the implementation of customized processing workflows and significant human intervention (Greer and Fomel, 2018). Moreover, a particular situation of interest emerges from the benefits of implementing diverse sources with specific bandwidth for enhancement purposes or innovative acquisition strategies such as DSA (Berkhout, 2012; Jeong et al., 2022; Acedo and Sacchi, 2023).

Leveraging LSTM capabilities to capture temporal and spectral dependencies, we developed a DL approach to merge prestack seismic datasets with different bandwidths into a coherent broadband volume. The proposed approach trains the LSTM neural network with the same data used for the inference and classifies it as a self-supervised method. Moreover, compared with other methods, it streamlines the process and minimizes user intervention. The following sections introduce the LSTM-based merging technique and validate the results by processing synthetic datasets.

Multi-source seismic data merging using LSTM neural networks

We deploy the LSTM neural networks to build a self-supervised method for bandwidth merging of multi-source seismic data. The methodology leverages the capabilities of LSTMs to handle sequential data with different bandwidths or spectral characteristics. In this approach, we incorporate layers of a bi-directional LSTM (Bi-LSTM) architecture (Schuster and Paliwal, 1997). Bi-LSTMs process data in both forward and backward directions, enabling the model to capture comprehensive contextual information from the input sequences for more accurate predictions. The procedure is self-supervised, as the network is trained with the same data for inference. Similar to the architecture presented by Roncoroni et al. (2024b) in processing GPR data, the architecture comprises three layers containing four (4), two (2), and one (1) Bi-LSTM layer and a single LSTM neuron for the output. The network takes three different input datasets (shots) acquired using different sources. Together with the architecture described above, these datasets are used in the training procedure. Once the network is trained, it can be applied to the input to generate a prediction, i.e., merged data with an equalized broader spectrum that combines the different sources. Training the neural network for merging applications entails implementing a custom loss function to weigh the contributions of the different frequency bands to the final volume. The objective function is expressed as

$$J = \sum_{k=1}^{n_s} \lambda_k ||\mathbf{X}_k - \hat{\mathbf{X}}||_2^2 \tag{1}$$

where $\mathbf{X}_k$ represents the shots acquired with different sources and $\hat{\mathbf{X}}$ contains parts of the input datasets after applying a masking function that eliminates a certain percentage of the data. The parameter λ_k is a weighting factor that evaluates each frequency contribution, assuming the frequency content is the main difference among the different sources implemented, and the data have been processed to have approximately the same phase. The subindex k represents the input datasets and goes up to n_s, the number of sources. Figure 2 depicts the training procedure.

Numerical experiments

The synthetic dataset comprises three seismic shots generated by band-passing a broadband signal to create narrowband signals with low, mid, and high-frequency content. We use these band-passed shots to input the Bi-LSTM network, keeping the same architecture presented in the previous section. In order to quantify the performance of the LSTM-merging procedure, we introduce the predictability metrics. Predictability is a measure of repeatability that is usually used to quantify the spectral match between seismic traces (Kristiansen et al., 2000)

$$PRED = \frac{\sum \Phi_{ab} \Phi_{ab}}{\sum \Phi_{aa} \Phi_{bb}}. \tag{2}$$

Since we are dealing with a scenario in which a ground-truth signal is compared to a merged signal, a small-lag range of ± 10 samples is appropriate to reflect how similar the traces are, assuming both should coincide in time. Predictability is not sensitive to statics, phase, or amplitude differences. However, it is mostly sensitive to noise and to changes in the reflectivity. Therefore, it can help to quantify and reflect the occurrence of missing events or signals in the result. Figure 3 displays the broadband seismic shot and the LSTM-merged obtained with the proposed method. The difference between the broadband and the LSTM-merged shot is also displayed. The predictability for this case is 0.87. As a reference, a value over 0.65 is usually considered good in time-lapse applications (Kragh and Christie, 2002). In Figure 3c, we observe some low-frequency leakage. As an additional quality control, Figure 4a displays the loss function against the number of epochs for a learning rate $\varepsilon = 0.01$, and Figure 4b compares the amplitude spectrum for the broadband shot and the LSTM-merged shot.

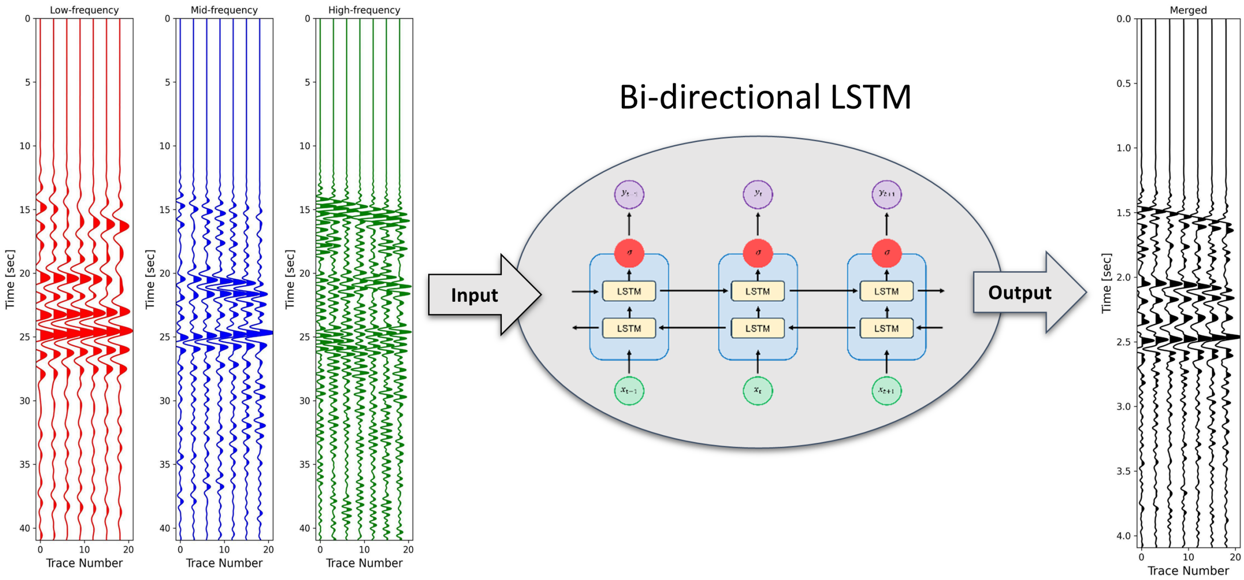

Figure 2: Sketch of the training procedure for the method of LSTM-merging. Three different input datasets (left) are used to train the LSTM-NN. The optimized weights are then applied to produce the broadband dataset (right).

Some low-frequency energy in the LSTM-merged shot is absent in the broadband shot. An energy spike in the mid-frequencies also pop-ups as a difference between the two spectrums. Despite these minor distortions and amplitude scaling, these results confirm that the proposed methodology effectively merges the original shots without introducing phase distortions or significant amplitude errors. The differences in the amplitudes are attributed to the limitations in the normalization procedure prior to the training and the values chosen for the frequency contribution of each dataset.

Conclusions

This article builds on Long Short-Term Memory (LSTM) neural networks to develop a method for bandwidth merging in multi-source seismic data acquisition. By leveraging the ability to handle sequential data and capture long-term dependencies, a self-supervised methodology demonstrates the versatility and efficacy of LSTM neural networks in bandwidth merging. The synthetic examples show that an LSTM-based method accurately merges signals with different frequency content into the broadband shot. Despite the slight amplitude scaling difference that generates the leakage in the difference plot, the method achieves high predictability scores, meaning the predicted signal resembles the truth signal. This study explores the potential of LSTM neural networks as an integral part of a method to streamline the merging of different datasets with minimum intervention.

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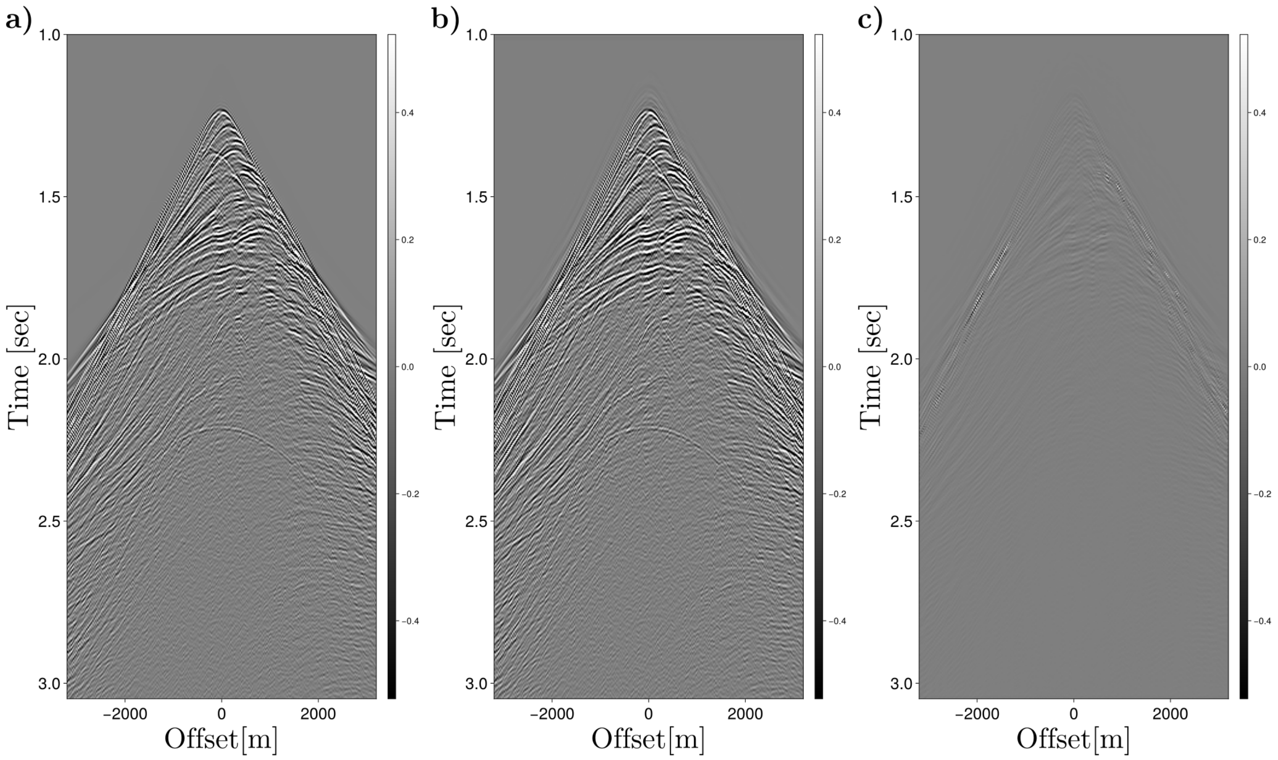

Figure 3: (a) Broadband shot used as ground-truth. (b) LSTM-merged shot. (c) Difference between (a) and (b).

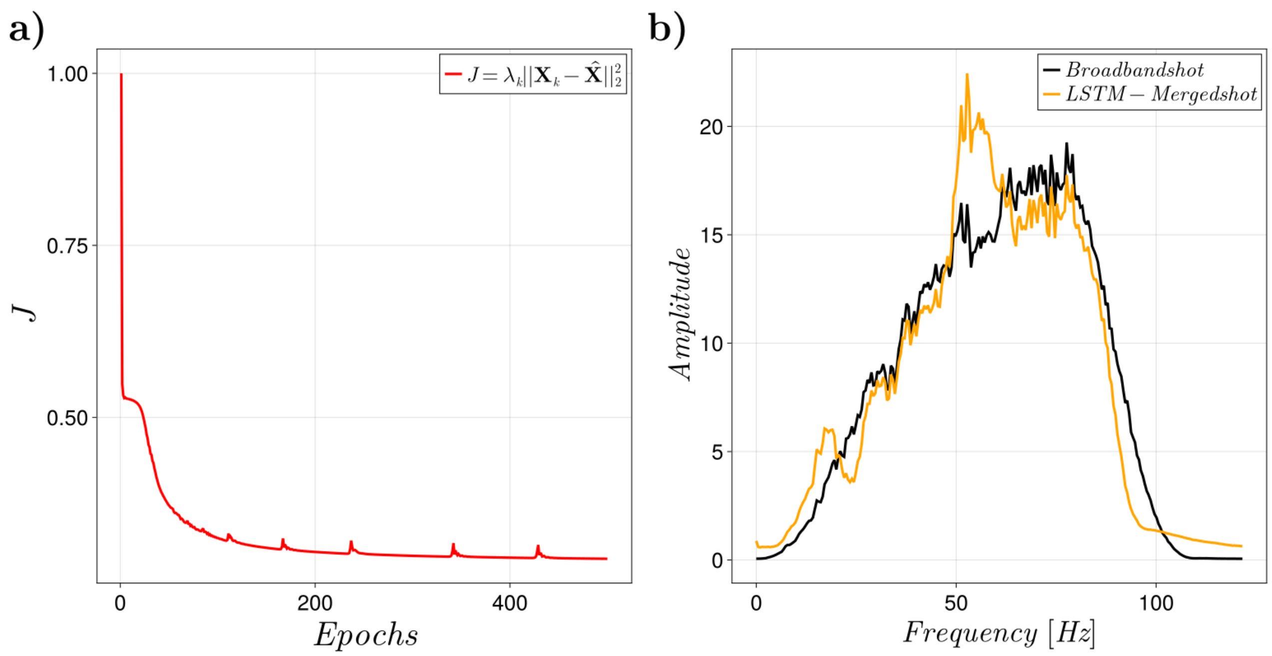

Figure 4: (a) Loss function versus number of epochs. (b) Comparison between the spectrum of broadband shot and LSTM-merged shot.

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